2017

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Published October 2017 in Engineering Applications of Artificial Intelligence 65:433-435
DOI: 10.1016/j.engappai.2017.09.001

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Introduction

Risks exist in every aspect of our lives, and can mean different things to different people. While negative in general they always cause a great deal of potential damage and inconvenience for stakeholders. Recent engineering risks include the Fukushima nuclear plant disaster from the 2011 tsunami, a year that also saw earthquakes in New Zealand, tornados in the US, and floods in both Australia and Thailand. Earthquakes, tornados (not to mention hurricanes) and floods are repetitive natural phenomenon. But the October 2011 floods in Thailand were the worst in 50 years, impacting supply chains including those of Honda, Toyota, Lenovo, Fujitsu, Nippon Steel, Tesco, and Canon. Human-induced tragedies included a clothing factory fire in Bangladesh in 2012 that left over 100 dead. Wal-Mart and Sears supply chains were downstream customers. The events of Bhopal in 1984, Chernobyl in 1986, Exxon Valdez in 1989, and the Gulf oil spill of 2010 were tragic accidents. There are also malicious events such as the Tokyo Sarin attach in

1995, The World Trade Center and Pentagon attacks in 2001, and terrorist attacks on subways in Madrid (2004), London (2005), and Moscow (2010). The news brings us reports of such events all too often. The next step up in intensity is war, which seems to always be with us in some form somewhere in the world. Complex human systems also cause problems. The financial crisis resulted in recession in all aspects of the economy. Risk and analytics has become an important topic in today's more complex, interrelated global environment, replete with threats from natural, engineering, economic, and technical sources (Olson and Wu, 2015).

Thus we need to engineer systems to reliably cope with the high levels of uncertainty induced by the complex systems we build. Using Artificial Intelligence techniques for engineering risk and analytics decisions is a fast-growing and promising multidisciplinary research area (Olson and Wu, 2017). AI techniques that are useful include, but are not limited to expert systems, artificial neural networks, support vector machines, evolutionary computations, fuzzy systems, knowledge based systems, case-based reasoning, agent-based models, and their hybrids, etc. For example, artificial intelligence models such as neural networks and support vector machines have been widely used for establishing the early warning system for monitoring a company's financial status. Agent-based theories are employed in supply chain risk management. Business intelligence models are also useful in hedging financial risks by incorporating market risks, credit risks, and operational risks. Investigation of business intelligence tools in risk management is beneficial to both practitioners and academic researchers. A new and promising approach is to hybridize AI techniques with operations research approaches (Schemeleva et al, 2012). The call for papers of this special issue asked for real world applications of risk management in engineering using artificial intelligence tools.

Artificial Intelligence in Engineering Risk Management

Since risk is inherent in human activity, risk management is needed in all aspects of human activity. This includes engineering, where catastrophes such as the Tacoma Narrows Bridge failure would be good to avoid. Artificial intelligence continues to evolve, and while some may question the ultimate limits to computer ability, others see great opportunities (Kurzweil, 2000; 2006). Conversely, artificial superintelligence could cause global catastrophe. Barrett and Baum (2017) discussed artificial superintelligence decision-making risk.

The application of artificial intelligence tools to engineering is widespread. Schneidewind (2009) reported risk management applicable to NASA Space Shuttle software risk prediction, using a cumulative failures gradient function. Wong and Qi (2009) used neural networks in program debugging to identify the exact location of program faults. Fuzzy systems have been used to create more robust wireless networks (Luo et al., 2009). More recently, systems to avert cyber intelligence threats have been developed using semantic text modeling (Qamar et al., 2017).

The energy sector involves many problems calling for risk management. Boonchuay and Ongsakul (2012) applied particle swarm optimization to assess bidding strategies for a power generation firm. Shariatinasab et al. (2014) used neural networks to replace simulation in evaluating lightning flashover outage avoidance strategies. Nuclear power risk assessment was supported by artificial intelligence models reported by Pourali (2014).

In the financial engineering domain, applications of artificial intelligence tools to improve investment risk management have existed for a long time. Mileris and Boguslauskas

(2010) reported data mining and factor analysis models for the well-studied application area of credit risk estimation. Simulated annealing was used for the same general problem by Li and Ng (2013). Chinese financial fraud risk was assessed by data mining algorithms to include neural networks by Song et al. (2014). Credit risk management practices were evaluated by Butaru et al. (2016) using machine learning.

There are many other domains of human activity where artificial intelligence risk management models have been applied. Text mining algorithms were used by Lee et al. (2013) in patent claim analysis. Ou et al. (2013) used neural networks to predict driver safety risk prediction. Zhou et al. (2016) applied Bayesian analysis models in a medical decision support system to aid expert judgment. In food security management, Chang et5 al. (2017) used Markov game theoretic models to avoid food contamination. Thus we see that practically every aspect of human activity involves engineering problems where artificial intelligence modeling can be fruitfully applied. Many problems requiring applications of such techniques in production systems, supply chains and logistics can be found in (Dolgui and Proth, 2010; Ivanov et al., 2017).

Journal Risk Management Applications

Engineering Applications of Artificial Intelligence has a history of publishing articles related to artificial intelligence in risk management. Fu (2011) reviewed data mining applications to time series. Wang et al. (2014) used grey models for prediction related to the largest video site in China. Sundarkumar and Ravi (2015) considered dataset balancing in customer credit card churn prediction. He et al. (2016) used fuzzy TOPSIS and rough sets for new product failure analysis.

Krishna and Ravi (2016) used evolutionary computer in support of customer relationship management. Finally, Gan et al. (2017) reported a means to improve data mining pattern recognition for time-based data.

Contents of Special Issue

This first half of this special issue includes five papers with current applications of artificial intelligence to real engineering problems. Chou applied artificial neural networks and other data mining models to deal with corrosion in concrete structures and steels in Taiwan. This is a highly nonlinear, complex problem, and a smart firefly algorithm was used with other models on two real datasets. This provides civil engineers with a superior means to schedule maintenance to reduce risk of structural failure. Datta provided a fuzzy set model to a metropolitan construction project involving an underground rail station in an Indian metro area. Pendharkar used data mining ensembles to improve posterior classification fit to real data in general. Luo applied deep belief networks to better assess credit scoring of credit default swaps. Finally, Silva, Santos, Bottura and Oleskovicz gave a neural network model to monitor voltage amplitude in an electrical distribution system in Brazil.

Thus we see a variety of useful artificial-intelligence related models being applied to real problems. This special issue includes five diverse applications utilizing a variety of artificial intelligence related tools. It is a pleasure to be able to provide readers access to these innovative and effective improvements in risk management in engineering.

ACKNOWLEDGMENT

The authors would like to thank all the referees and the Editor-in-Chief A. Abraham, for their energy and efforts in bringing out this special issue. This work is supported by the Ministry of Science and Technology of China under Grant 2016YFC0503606, by National Natural Science Foundation of China (NSFC) grant [grant nos. 71471055; 91546102], by Chinese Academy of Sciences Visiting Professorship for Senior International Scientists [grant number 2013T2J0054], by Chinese Academy of Sciences Frontier Scientific Research Key Project under Grant No. QYZDB-SSW-SYS021 and by Chinese Academy of Sciences Strategic Research and Decision Support System Construction Special Grants GHJ-ZLZX-2017-36.

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